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Social Learning, Neighborhood Effects, and Investment in Human Capital: Evidence from Green-Revolution India

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Abstract

This paper empirically identifies social learning and neighborhood effects in schooling investments in a new technology regime. The estimates of learning-investment rule from farm household panel data at the onset of the Green Revolution in India, show that (1) agents learn about schooling returns from income realizations of their neighbors and (2) schooling distribution of the parents' generation in a community has externalities to schooling investments in children that are consistent with social learning. Simulations show that variations in schooling distributions within and across communities generate through social learning substantial variations in child enrollment rate and average household income. The results suggest that imperfect information hinders investment in human capital.

Key words: human capital, social learning, neighborhood effects, income risk, schooling distribution, technical change, India

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1. Introduction

It is increasingly recognized that technological changes affect returns to schooling in both developing and developed countries (e.g., Foster and Rosenzweig 1996; Juhn, Murphy, and Pierce 1993). To correctly infer new returns, however, agents face an informational problem. Since schooling investment is irreversible and also requires a long gestation period, agents cannot simply go to school to learn about schooling returns. Instead, they must use observations from others to infer these returns. When agents learn from their neighbors, neighborhood factors influence the social learning.

Thus, the neighborhood is where agents learn from their neighbors. This paper examines neighborhood effects on the social learning that determines schooling decisions. The authors use household data available from the onset of the Green Revolution in India, where in some regions the diffusion of high-yielding varieties (HYVs) affected returns to schooling. The analysis shows that the schooling distribution of the parents' generation in a neighborhood is important to social learning and household decisions regarding child schooling investments.

The empirical finding that schooling decisions are correlated among neighbors can be viewed as the evidence of neighborhood effects, peer pressure, role models, norms of behavior, and social networks. The high correlation of similar decisions among neighbors has been found in many empirical studies (Case and Katz 1990; Evans, Oates, and Schwab 1993; Strauss and Thomas 1995; Topa 1997; Conley, Flyer, and Tsiang 1999). Moreover, within-community correlations are hypothesized to justify public subsidies for education in theoretical studies (Benabou 1996).[1] However, the process that generates the cross-sectional correlations of decisionmaking has not been empirically

[1] The literature in bounded-rationality social learning (Ellison and Fudenberg 1993) analyzes different types of myopic learning rules (rules of thumb), asking if the equilibrium converges to an efficient outcome in the long run. Inertia is assumed in the dynamics of endogenous variables. Most of the empirical studies confirming contemporaneous cross-agent correlations share the same spirit of abstraction with this literature in that behavioral foundations are not clarified. This paper, on the other hand, assumes rational (Bayesian) learning and attributes spatial variations of outcomes to different environmental factors (neighborhood characteristics) that determine the speed of learning.

identified until recently, except by Besley and Case (1994), Foster and Rosenzweig (1995), Munshi (2004), and Conley and Udry (2004)[2]. This study attempts to empirically identify the process of social learning and neighborhood effects on child schooling investments in a Bayesian learning model.

The question of whether agents know of and how fast they respond to return structures poses a more extensive but fundamental question into the way we think about economic development. For example, are observed variations of human-capital accumulation simply a consequence of different return-augmenting mechanisms in perfect information, as argued in endogenous growth theories (Lucas 1988; Romer 1986)? Or are they a consequence of local environments that affect agents' learning speed under imperfect information? Even if returns are augmented, the latter would generate substantial variations in investment. Though corresponding implications for development policy differ, it is not easy to identify these two cases through casual observations.

Empirical findings regarding the above question are inconclusive. In his extensive survey on the rate of return to schooling investments, Psacharopoulos (1994) points out higher rates of return to private schooling investments in developing countries than in developed countries, especially from primary education. Child schooling investments are likely to be suboptimal in less-developed countries, although in most studies he surveys, the sampling is not random and sometimes selective.[3] The evidence on dynamic changes in enrollment rate is rare in the literature on developing economies. Foster and Rosenzweig (1996) and Rosenzweig (1990) are exceptions. They show evidence from India that private schooling investments have increased in 10 years in regions where technical change was rapid and therefore, they argue, schooling returns

[2] This paper does not incorporate networks of neighbors that determine exact routes of information flow in a community, as in Conley and Udry (2004). It is assumed in this study that households in a village can observe all the neighbors in the village and that they give equal weight to information from all their neighbors.

[3] Glewwe (1996) argues that it is important to incorporate quality adjustment in schooling investments in the empirical assessment of schooling attainment. See, also, Behrman (1999) for a recent survey of empirical evidence from broader perspectives.

were augmented.[4] Given the change in returns to schooling, however, it is not clear how precisely agents inferred the true returns immediately after returns changed and, if social learning was important, how agents learned about the returns and responded with investment behavior to altered environments.

Among empirical tests for learning externalities, a few studies have explicitly incorporated sequential updating of agents' perception.[5] In the literature, social learning was identified in the context of technology adoption in agriculture.[6] To estimate the adoption rule of HYV with learning externalities, Besley and Case (1994) uses a risk-neutral Bayesian framework in which agents infer the mean profitability of HYV from their neighbors. On the other hand, Foster and Rosenzweig (1995) adopt a modified target-input Bayesian model in which agents learn the best uses of inputs with the new technology and showed that farmers are learning from both their own experiences and those of neighbors. In the target-input framework, Rosenzweig (1995) also shows that schooling hastens farmers' learning speed in HYV adoption.

While the above studies assume that reference groups for agents are geographical clusters such as villages, Conley and Udry (2004) incorporates agents' networks explicitly based on actual information flows in pineapple adoption behavior in Ghana. They show that it is not geographical proximity but rather information networks that

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[4] See, also, a seminal article by Schultz (1975) for discussions on the relationships between technical change, education, and schooling returns. He argues that returns to ability to deal with disequilibria increase at the time of technical changes. Although Foster and Rosenzweig (1996) does not specify the time period in which returns to schooling remain augmented due to a technical change, the advantage of being educated may cease once knowledge of new technologies diffuses completely.

[5] Another strand of study is the econometric literature of reflection problems (e.g., Manski 1993a, 1993b; Case and Katz 1990). This class of study focuses on a static relationship of agents' perception and decisionmaking, ignoring possible dynamic adjustments of perception (i.e., learning). Once a reference group is identified using researchers' prior knowledge, the dynamic formation of agents' perception is factored out from the analysis. Under the assumption of stationarity, researchers can estimate the conditional distribution function of schooling returns from a large sample of income realizations, which under rational expectations enables them to assess agents' schooling decision rule.

[6] See Besley and Case (1993) for a summary of possible modeling strategies to analyze the technology diffusion process. There seem to be two estimable structural modeling strategies: the updating of mean priors under risk neutrality and the target-input model under quadratic loss function. Besley and Case focus on the former.

significantly enhance social learning.[7] The importance of reference-group identification is emphasized by Manski (1993a) in his seminal work.

Munshi's (2004) study is related to this paper in his attempt to identify the role of unobserved heterogeneity in determining the efficiency of social learning in the context of farmers' HYV adoption in rice and wheat productions. His results show that farmers may learn less from others when production is more sensitive to farm-specific idiosyncratic factors, and that unobserved heterogeneity is more important.

One conclusion of this paper is that heterogeneity helps agents learn. While Munshi examines heterogeneity that is unobservable (and idiosyncratic) to agents, this paper examines heterogeneity that is observable. In an analogous way, error terms (i.e., unobserved heterogeneity) in econometric estimation deter precise parameter estimates, while the variations in explanatory variables (i.e., observed heterogeneity) help estimate parameters precisely. The details will be described in Section 2.

In this paper, I assume that households are attentive to the expected returns to schooling, i.e., that agents are risk neutral. An alternative modeling strategy would be to use a target-input framework, as in Foster and Rosenzweig (1995). The target-input framework is suitable for identifying learning externalities if the externalities affect input allocation decisions and therefore the actual profitability of investment in the context of HYV adoption. However, the informational spillovers from neighbors should only influence agents' perceptions on their future income gains—returns—in the context of schooling investments in children. The income gain from advancing to a higher level of education will be realized only in the future, after agents complete the education. The returns will be realized when agents accumulate their labor-market experience. Hence, learning about schooling returns does not lead to changes in profitability or income at the time the decision is made. In the framework of this paper, I therefore model social

[7] Conley and Udry (2004) uses spatial standard errors that incorporate the spatial dependence of error terms. In our data, residential locations of households are only identified by villages and inter-household geographical proximity is not known. Villages are geographically distant from each other in our data. Moreover, the data contain no measures of the density of actual information networks.

learning and investment behavior such that learning externalities change agents' perceptions of future income gain and agents change their schooling decisions in response to changes in their perceptions, but informational spillover is neutral to current incomes that directly influence the current welfare of agents.

The following two points need careful attention. First, in any kind of test for externalities, it is important to exclude the possibility that observed cross-agent correlations of schooling decisions are spurious, i.e., driven by common unobservable factors. For example, variations in schooling investment can be attributed to unobserved heterogeneous local endowments and preference for education. Since unobserved factors are often strongly correlated with observable factors, we can easily infer a spurious correlation between observables and schooling investments. Any empirical analysis must meet the challenge of identifying learning externalities against common unobservables.

Second, both social learning and learning-by-doing lead to similar observable implications. The observation that schooling investments are positively correlated with an income gap between the educated and the uneducated does not necessarily imply social learning. Suppose that to find the best manager among household members, the household experiments by assigning each member in turn to the manager. In villages where schooling returns are increased, households eventually discover that the best farm manager is the most educated member. In this scenario, information from neighbors plays no role. To distinguish social learning from this within-family learning-by-doing, it is therefore imperative to examine not only the relationship between schooling return signals and schooling investments, but also the process by which neighborhood factors affect social learning, with a theoretical framework to interpret empirical findings.

In the next section, a theoretical framework is formulated to provide a basis for the empirical analysis. Agents learn about schooling returns from income difference between educated and uneducated households (schooling return signals, hereafter). It is shown that agents' learning speed is influenced by neighborhood conditions such as income uncertainty and schooling distribution of the parents' generation. Section 3 describes the empirical strategy. Instead of tracing agents' learning process, I estimate

schooling returns in farm profit function, using ex post information on the impact of technical change on schooling returns. At the onset of the Green Revolution in India, HYVs were available to some regions, which caused changes in schooling returns in some sample villages. Section 4 describes farm household panel data from India, which I use in the empirical analysis. The Additional Rural Incomes Survey (ARIS) was conducted by the National Council of Applied Economic Research (NCAER) in three crop years, 1968-69, 1969-70, and 1970-71, which correspond to the onset of the Green Revolution, when at least in some districts, farmers experienced changes in schooling returns (see Rosenzweig 1990).

Section 5 summarizes empirical results. First, schooling investment is positively correlated with the income difference between educated and uneducated households. The finding is consistent with social learning. Second, schooling distribution of the parents' generation in a village influences the response of school enrollment to schooling return signals—that is, agents' learning speed—in a manner consistent with theoretical predictions on social learning. Local schooling distribution of the parents' generation has intergenerational externalities to schooling investments in children.

In Section 6, I simulate paths of enrollment rate and average household income, based on the estimated learning-schooling investment rule. Simulations show that school enrollment rate would increase by about 3 percentage points in five years if the proportion of educated households in a village increases from 0 to 0.53. Since educated households have, on average, a higher income than uneducated households, a disparity of average household income would emerge over the five years. Thus, the initial distribution of schooling—which differs across communities—determines the evolution of income inequality over space. The analysis also has some aggregate implications: reallocating agents across communities can improve the aggregate response of schooling investments to a change in returns. This economy-wide implication is also quantified based on the estimated parameters. The final section summarizes the findings of this paper and discusses further implications.

2. Model

In this section, I formulate a two-stage model and derive empirical implications. In the first stage, agents observe income realizations of their parents and neighbors and make schooling choices. When agents decide schooling investments, they face subjective uncertainty in the inference on returns to schooling.[8] Uncertainty is resolved in the second stage.

The Environment

Time is discrete and refers to year ($t = 1, ..., T < +\infty$). In each community, children who are randomly born decide their schooling level at an exogenously given age, using observations of income realizations of neighbors, including their parents.[9] For simplicity, assume that both boys and girls have identical returns to schooling. Risk-neutral agents (children) at the age to decide schooling investments in time *t* choose a high level of education h^H or a low level of education h^L where $h^H > h^L$, which provides a higher lifetime expected income.[10]

Neighbors' incomes, from which agents learn about schooling returns, are given as

$$y^s_{j,t} = \theta^s + v_t + \xi_{j,t}, \tag{1}$$

where $y^s_{j,t}$ is farm profit per unit of land for household *j*, in year *t* and with schooling *s* = *H* or *L*, θ^s is an unknown returns to schooling investment of level *s*, $\xi_{j,t} N\left(0, \sigma^2_\xi(s)\right)$

[8] In a seminal article, Schultz (1961) argues the importance of assessing uncertainty on the future outcome of education in private schooling decisions.

[9] Since the timing of the decision is fixed, strategic interactions of investment decisions are assumed out. Whether parents or children themselves make schooling decisions is also trivial, if parents cannot change their schooling levels.

[10] I may incorporate sequential or multiple-choice decisionmaking. However, since the current setting suffices to provide basic intuitions, I will focus on this binary-choice model.

is an idiosyncratic shock to j, and $v_t N\left(0,\sigma_v^2\right)$ is a village-specific aggregate transitory shock.[11] Assume that $\sigma_{\xi}^2(H) \neq \sigma_{\xi}^2(L)$. Let τ denote technical change that potentially alters returns to schooling. Assume that agents cannot predict locations of technical change ex ante and therefore cannot move with the anticipation of future technical change.[12] Also assume that the values of schooling returns, θ^H and θ^L (therefore, the value of their difference), are unknown ex ante.

Assume that parents and children can observe current income realizations in equation (1) and schooling distributions $\{y_{i,t}^s, h_i\}$ for all agents i in their community. Their problem is to infer schooling returns from $\left\{y_{i,t}^s\right\}$ for all i. We omit τ until the discussion on empirical strategy.

Risk-neutral children choose h^H at t if the expected value of net returns for h^H is larger than that for h^L in the second stage.

$$E\left[y_j^H \mid \Omega_t^j\right] - \left(1+r_j\right)b_j - \overline{c} + b_j \geq E\left[y_j^L \mid \Omega_t^j\right] + w_c, \tag{2}$$

where Ω_t^j is information set for agent j at t, $\overline{c}$ is the cost of advancing schooling investment to a higher level (e.g., transportation cost, increasing as distance to school increases), b_j is credit borrowed for financing schooling investments, r_j is interest rate for household j, and w_c is child wage (i.e., opportunity cost). Assume that the interest rate is increasing and convex in the amount borrowed and decreases in landholding size, such

[11] Alternatively (Yamauchi K., 1998), ability heterogeneity in income process can be incorporated as follows: ability is defined as the probability that a task is done successfully, $q_j = prob(a_{j,t} = 1)$, where $a_{j,t}$ takes the value of 1 if the task is done successfully. Income process is written as

$$y_{j,k,t} = a_{j,t}\theta^k + d_j\left(v_t + \xi_{j,t}\right).$$

In this setting, complementarity of ability and schooling exists. Ability defines a likelihood that schooling matters in income determination. Agents learn about q_j and $\Delta\theta$ from income realizations of parents and neighbors. In this framework, however, econometricians face a rather involved inference problem due to the unobservability of $a_{j,t}$.

[12] Returns to schooling may be positive only temporarily and converge to zero as time passes after a structural change. However, if there is a strictly positive probability for a structural change, the expected returns to schooling can be positive.

that $r_j = r\left(b_j, d_j\right)$ with $\partial r/\partial b > 0$, $\partial^2 r/\partial b^2 > 0$, and $\partial r/\partial d < 0$. The cost of borrowing is smaller for large landowners since they have smaller default risks. Assume that agents finance the educational investment by borrowing from the credit market, i.e., $b_j \geq \overline{c}$ if h^H is chosen. The optimal borrowing rule is $b_j^* = \max\left\{\overline{c}, b^*\left(d_j\right)\right\}$ and $b^*\left(d_j\right)$ satisfies the first order condition:

$$r\left(b_j, d_j\right) + \frac{\partial r\left(b_j, d_j\right)}{\partial b_j} b_j = 0.$$

Therefore, the condition for schooling investment is

$$E\left[\theta^H - \theta^L \mid \Omega_t^j\right] \geq c\left(d_j\right), \tag{3}$$

where $c(d_j) = \overline{c} + w_c + \left[\left(1 + r\left(b_j^*, d_j\right)\right) - 1\right] b_j^*$. The direct and indirect cost of schooling investment $c\left(d_j\right)$ is strictly decreasing in d_j when $b_j^* = \overline{c}$, and can be either increasing or decreasing in d_j if $b_j^* > \overline{c}$. In the next section, I specify the conditional expectations in the left-hand side of equation (3) using Bayesian learning.

Social Learning

Bayesian learning gives a theoretical foundation for the following empirical analysis. In the empirical setting of this paper, social learning is defined as learning about the unknown schooling-return gap θ^H - θ^L from income realizations in the neighborhood. Assume that the prior mean of the return gap follows $N\left(\mu_t, \sigma_t^2\right)$. Under the assumption that v_t and $\xi_{j,t}$ are also normally distributed, the posterior mean on the return is written as

$$E\left[\theta^H - \theta^L \mid \Omega_t^j\right] = \mu_t + W\left(x, \sigma_t^2\right)\left[\left(\overline{y}_t^H - \overline{y}_t^L\right) - \mu_t\right], \tag{4}$$

where schooling return signal is

$$\bar{y}_t^H - \bar{y}_t^L = \theta^H - \theta^L + (\bar{\xi}_t^H - \bar{\xi}_t^L). \tag{5}$$

Prior mean is updated with additional information from the realized average incomes among educated and uneducated households. Note that signals are unbiased, i.e.,

$$E\left[\bar{y}_t^H - \bar{y}_t^L\right] = \theta^H - \theta^L .^{13}$$

The learning weight $W(x, \sigma_t^2)$ in equation (4) is written as

$$W(x, \sigma_t^2) = \frac{\sigma_t^2}{s(x) + \sigma_t^2} \in [0,1), \tag{6}$$

where $s(x)$ is noise variance, i.e.,

$$s(x) = \frac{1}{N}\left(\frac{a}{n} + \frac{1}{1-n}\right)\sigma_\xi^2(L),$$

---

[13] In the case that $y_{j,k,t} = \theta^k(\tau) + d_j(v_t + \xi_{j,t})$, sampling strategy is sensitive to the distribution of landholding size in a finite population and to the variances of aggregate and idiosyncratic shocks. There is a trade-off between additional value from new information and an increase in noise. If there are variations in landholding size within a group, agents need to choose a subset of agents from each group to minimize the variance of noise in signals. To clarify this point, we consider two extreme situations. In the case that $\sigma_\xi^2 = 0$ and $\sigma_v^2 > 0$, it is the optimal strategy to sample observations from the two groups of neighbors such that $\frac{\sum_{i\in H} d_i}{N_H} - \frac{\sum_{i\in L} d_i}{N_L}$ is as close to zero as possible. Note that both N_H and N_L are endogenous here. In this way, the adverse effect of aggregate risks would be minimized. Second, in the case that $\sigma_v^2 = 0$ and $\sigma_\xi^2 > 0$, it is the optimal strategy to sample observations from the smallest landholding size as far as $\left(2 + \frac{1}{N_k}\right) > \frac{d'^2}{\bar{d}^2}$ where $\bar{d}^2 = \frac{1}{N_k}\Sigma_{i\in k}\, d_i^2$ and d' is the landholding size of the $(N_k + 1)^{\text{th}}$ neighbor in group k. If the distribution of landholding sizes is concentrated in a narrow range in each group, sampling from all the neighbors is the best sampling strategy.

where n is the proportion of educated households, N is the total number of households, a is the ratio of idiosyncratic shock variances of the educated to the uneducated ($a = \frac{\sigma_\xi^2(H)}{\sigma_\xi^2(L)}$), and x denotes a vector of neighborhood characteristics $(a, n, N, \sigma_\xi^2(L))$. In equation (4), $W(x, \sigma_t^2)$ measures how efficiently the prior mean incorporates new information.

Since the prior variance σ_t^2 asymptotically converges to zero, $W(x, \sigma_t^2)$ also converges to zero, which implies learning speed is high in the initial periods but decreasing over time. However, learning speed depends on community characteristics x.

By equations (3), (4), (5), and (6), $E\left[\theta^H - \theta^L \mid \Omega_t^j\right]$ in equation (3) is obtained as a lag polynomial of observed return signals.

$$E\left[\theta^H - \theta^L \mid \Omega_t^j\right] = W_t\left(x, \sigma_t^2\right) \sum_{r=1}^{t} (\overline{y}_r^H - \overline{y}_r^L) + \varphi_t \mu_0 , \tag{7}$$

where $\varphi_t = \Pi_{r=1}^{t}\left(1 - W_r\right)$ decreases over time. Assume that the initial prior μ_0 is randomly distributed across communities, so $\varphi_t \mu_0$ can be treated as an error term. The second equality comes from the updating of the prior variance.[14] If $\mu_0 = 0$ and $\theta^H > \theta^L$, the expected value of the perceived return gap on average increases over time.[15]

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[14] Since noise variance $s(x)$ is time invariant, we have $\frac{\sigma_{t+1}^2}{\sigma_t^2}\left(\frac{1-W_{t+1}}{W_{t+1}}\right) = \left(\frac{1-W_t}{W_t}\right)$. On the other hand, the prior variance updating provides $\frac{\sigma_{t+1}^2}{\sigma_t^2} = 1 - \omega_t$. Therefore, the relationship between learning weights of t and $t + 1$ is given as $W_{t+1} = W_t\left(1 - W_{t+1}\right)$.

[15] To see this, note that signal $(\overline{y}_r^H - \overline{y}_r^L)$ is unbiased, so the left-hand side of equation (8) is

$$W_t E \Sigma_{r=1}^{t} (\overline{y}_r^H - \overline{y}_r^L) = W_t \Sigma_{r=1}^{t} (\theta^H - \theta^L) = W_t t(\theta^H - \theta^L) . \tag{8}$$

It is sufficient to characterize $\omega_t t$. Define $g(t) = W(t)t$ and, for approximation, assume that it is differentiable, $g'(t) = W(t) + tW'(t)$, where $W' < 0$, $W'' > 0$, and $W(t) \to 0$ as $t \to \infty$. Therefore, $g'(t) > 0$ if elasticity of $W(t)$ is less than 1, as shown $\left|\frac{W'(t)t}{W(t)}\right| < 1$. Since W_{t+1} - $W_t \in (0,1)$ for all t, the elasticity is less than 1 and $g'(t) > 0$.

In this case, we expect that school enrollment increases over time but at a diminishing rate.

Learning weight W_t defines the adjustment speed of agents' perceptions on schooling returns. In the empirical analysis of this study, the characterization of learning speed also provides neighborhood effects that arise from social learning. Thus, the effect of schooling return signals on schooling investments depends on neighborhood characteristics and therefore can differ across communities. The following proposition summarizes neighborhood effects.

Proposition 1. Learning Speed: Identification of Neighborhood Effects—Social Learning

(i) The speed of adjustment in agents' perception on schooling return differential, defined as W_t, is decreasing and convex in income volatility.

(ii) The adjustment speed is concave in the proportion of the educated in community population, and there exists the maximum at

$$n^* = \frac{a}{1+a} \in (0,1).$$

Moreover, n^* is increasing in a, ratio of idiosyncratic shock variances for the uneducated to the educated.

Proof. (i): Directly follows from the first and second derivatives of equation (6) with respect to $\sigma_\xi^2(L)$ and to N.

(ii): n enters only in $\frac{1}{N}\left(\frac{a}{n}+\frac{1}{1-n}\right)$. By differentiating W_t with respect to n,

$$\frac{\partial W_t}{\partial n} = \frac{-1}{N}\left(\frac{\sigma_\xi^2(L)}{Den_t^2}\right)\left[-\left(\frac{a}{n}\right)^2+\left(\frac{1}{1-n}\right)^2\right],$$

where Den_t denotes $1+\frac{1}{N}\left(\frac{a}{n}+\frac{1}{1-n}\right)\sigma_\xi^2(L)$. Therefore, $\frac{\partial W_t}{\partial n} \le 0$ if $n \ge n^* \equiv \frac{a}{1+a}$, and $\frac{\partial W_t}{\partial n} > 0$ if $n < n^*$.

Q.E.D.

Here the effects of (i) income risks and (ii) schooling distribution of the parents' generation are highlighted. These neighborhood factors characterize learning speed, i.e., responsiveness of agents' perceptions to signals. Implications are quite intuitive in terms of simple regression problem.

First, income uncertainty magnifies noise in observations, which hinders agents' learning. In a risky and therefore less informative environment, it is difficult for agents to decipher the true return from incomes, since incomes fluctuate stochastically.

Second, there exists in each community a unique schooling distribution, the proportion of educated households, which maximizes learning speed. Heterogeneity (inequality) rather than homogeneity (equality) of schooling levels *in a community* facilitates social learning. Intuitively, if population is heterogeneous in observable characteristics, it is easy for agents (and researchers) to correctly decipher income difference that attribute to the difference in those observable characteristics. This point is analogous to the role of variations in explanatory variables in regression analysis, in which income level is regressed on years of schooling. The slope coefficient measures schooling returns. As the years of schooling (explanatory variable) vary *in a sample*, the estimate becomes more precise (and therefore more efficient).

The optimal proportion of the educated depends on income-shock heteroskedasticity between the educated and uneducated. If income shock variance is larger for educated farmers than for uneducated farmers (i.e., larger a), the income process for the educated contains more noise. In this case, n^* must increase to hasten learning speed as a larger sample size from the educated offsets the adverse effect of noise in their incomes.

3. Specification, Identification, and Estimation

In this section, I describe the empirical strategy with focus on specification and identification issues.[16] There are two possibilities in empirical strategy. I may trace agents' learning and sequential decisionmaking. Signals for agents can be approximated as residuals from profit function, which includes information on unknown returns to schooling. This approach was attempted in Yamauchi (1998). However, by construction, the residual-based return signals may contain unobserved factors that are potentially correlated with education, which biases the returns upward. Moreover, if parents' education is positively correlated with child schooling, it is easy to infer a positive correlation between the residual-based return signal and child schooling.

In this paper, I can directly estimate schooling returns that agents learn about with which to identify schooling decisions. The basic strategy involves two stages. In the first stage, I identify farm profit function, including the effect of education. It is possible to check whether schooling returns had changed when HYV became available in some villages. I estimate (1) village-specific schooling returns separately for each village, and (2) the impact of HYV adoption on schooling returns, from which to construct village-specific schooling returns. I focus on the first approach in the main analysis, and check the robustness with the second approach.

In the second stage, I estimate the learning-investment rules with the estimates of schooling return signals constructed from the first stage, incorporating theoretical predictions on neighborhood effects. Identification for social learning versus learning by doing is discussed in the end of this section.

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[16] In general, it is important for observers (researchers) to (1) make a distinction between what economic agents know and do not know and (2) know what researchers can identify (available from data). In general, information set available to researchers is smaller than information set for economic agents. In some events, however, it is possible to identify parameters that agents did not know, using ex post information contained in data.

Construction of Signals from Profit Function

Farmers know the pre-Green-Revolution structure of their profit function. It is assumed that, before the Green Revolution, schooling did not matter in farm profit. The profit function before t_0 is

$$y_{j,t} = \sum_{i=1}^{n} \beta_i m_{j,t}^i + \alpha_j + v_t + \xi_{j,t}, \tag{9}$$

where $\{m_{j,t}^i\}_i$ includes farm capital stocks such as irrigation assets, farm equipment, and livestock, and α_j is the unobserved endowment heterogeneity that affects land productivity $y_{j,t}$. The information set of farmers at t_0 contains $\{\beta_i\}_{i=0}^n$ and $\left\{\alpha_j\right\}_j$. After t_0, however, the profit function has schooling effects. Therefore,

$$y_{j,t} = \sum_{i=1}^{n} \beta_i m_{j,t}^i + \alpha_j + \theta_v^s + v_t + \xi_{j,t}, \tag{10}$$

where θ_v^s is village v-specific returns on s^{th} level of schooling. The key informational assumption here is that θ_v^s is unknown for agents and therefore for econometricians too.

I estimate the marginal effect of $I(s_j = H)$ on farm profit per unit of cropland for each village separately, where $I(s_j = H)$ takes the value of one if the highest level of education among household members is higher than primary and zero otherwise. I control irrigation asset, adverse weather indicator, and year effects. In this approach, I must assume that household fixed effect α_j is uncorrelated with $I(s_j = H)$. Since education was determined prior to the Green Revolution, it is unlikely to be correlated with profit shocks, but it could be potentially correlated with unobserved household-level fixed components within the village. In this estimation, I include irrigation asset per unit of cropland and year fixed effects.

To check the robustness of the major findings, the estimated village-specific returns are regressed on the initial-year average HYV adopted. In this exercise, we

assume Foster and Rosenzweig (1996) results that HYV availability increased the returns to schooling.[17] I take a simple approach estimating γ in $\hat{\Delta\theta}_v = \gamma_0 + \gamma \bar{HYV}_{v,0} + \eta_v$ where v denotes village, from which to construct $\hat{\gamma}\bar{HYV}_{v,t}$ as measures of returns attributable to village-level technical changes.

Estimation of Learning-Investment Rule

I estimate child school enrollment rate equations. From equation (8), the schooling-investment equation is

$$h_{j,\tau} \cong W_\tau(n,\sigma^2) \sum_{r=1}^{\tau} \hat{\Delta\theta}_r + \varphi_t \mu_0 + \phi_j + \varepsilon_{j,\tau}, \tag{12}$$

where $h_{j,\tau}$ is child enrollment rate for household j, μ_0 is unobserved initial prior mean, ϕ_j is a fixed effect, and $\varepsilon_{j,\tau}$ is measurement errors and shocks of $h_{j,\tau}$. We include a set of

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[17] Rather than estimating profit function with the interaction of HYV and schooling in differenced form using instruments,

$$\Delta y_{j,(t+1,t)} = \sum_{i=1}^{n} \beta_i \Delta m^i_{j,(t+1,t)} + \gamma_0 \Delta\tau_{j(t+1,t)} + \gamma_1 \Delta\tau_{j(t+1,t)} I(s_j = H) + \Delta u_{j,(t+1,t)}. \tag{11}$$

If farmers face borrowing constraints, there arises a positive correlation between current profit shocks ($u_{j,t}$) and the next period's stock ($\{m^i_{j,t+1}\}_i$), although this point is not explicitly incorporated in the model, namely, $E\left[\Delta m^i_{j,(t+1,t)} \Delta u_{j,(t+1,t)}\right] < 0$ and $E\left[\Delta\tau_{j(t+1,t)} \Delta u_{j,(t+1,t)}\right] < 0$. Therefore, this correlation makes the estimates β and γ and biased downward. To consistently estimate parameters in equation (11), I use the vector of instruments Z_j that satisfy the following conditions: $E\left[Z_j \Delta u_{j,(t+1,t)}\right] = 0$, $E\left[Z_j \Delta m_{j,(t+1,t)}\right] \neq 0$, and $E\left[Z_j \Delta\tau_{j(t+1,t)}\right] \neq 0$. For this purpose, the initial capital stocks and various village characteristics are used as instruments under the assumption that, before the beginning of initial period t_0, agents were not able to foresee the t_0 structural change and therefore could not change their capital stocks and village-level characteristics. In other words, technical changes occurred randomly and that agents did not alter their behavior and environments prior to the Green Revolution. I can construct $\hat{\Delta\theta}_t = \hat{\gamma}_1 \bar{\tau}_t$, where $\bar{\tau}_t$ is the village-average HYV adoption (per cropland). However, the lack of effective instruments specific for HYV adoption and schooling makes the estimation results inconclusive. See Foster and Rosenzweig (1996), who innovatively used the inherited asset for this purpose. Without such an identifying instrument, I would not pursue the above approach.

control variables such as the proportion of educated households, risk variance (n,σ^2 defined specifically below), household-level demographics, and village-level factors.[18] Assume that μ_0 has zero mean and a finite variance.

In our main analysis, we use standard errors of returns estimates obtained in the first stage to assess σ^2. This reflects the agents' estimation uncertainty regarding the returns to schooling specific to each village. In the second approach, we do not use this measure but only examine the implications on the proportion of educated households.

To construct the proportion of educated households for each village, within-village (interpretable) sampling weights are used. Let ϖ_j denote the sampling weight for household j. Then

$$n = \frac{\sum_j \varpi_j I\left(s_j = H\right)}{\sum_j \varpi_j},$$

where H and L denote groups of the educated and uneducated, respectively.

Return signals $\hat{\Delta\theta}$ can be correlated with community unobservables ϕ_j, e.g., the presence of good school and qualified teachers. It is therefore necessary to eliminate ϕ_j from the specification. In other words, I need to eliminate the possibility that fixed community factors lead to erroneously inferring social learning effects. For this purpose, a difference of equation (12) is taken between τ and 0 for estimation.

[18] This includes gross cropland in the initial period, the numbers of males aged 14 or above, females 14 or above, boys 10-14, girls 10-14, children 5-9, and children 1-4, the indicator of the highest schooling level in household being above primary, school indicator, the estimated number of farm households, village population, heath center indicator, modernity index, electricity, farm electricity, income decile, and expenditure decile.

$$\begin{aligned}\Delta h_{j(\tau,0)} &= W_\tau\left(n,\sigma^2\right)\sum_{r=\tau-p+1}^{\tau}\hat{\Delta\theta}_r \\ &+\left[\frac{W_\tau\left(n,\sigma^2\right)}{W_{\tau-p}\left(n,\sigma^2\right)}-1\right]W_{\tau-p}\left(n,\sigma^2\right)\sum_{r=1}^{\tau-p}\hat{\Delta\theta}_r \\ &+\left(\varphi_\tau-\varphi_{\tau-p}\right)\mu_0+\Delta\varepsilon_{j,(\tau,0)} \\ &=W_\tau\left(n,\sigma^2\right)\sum_{r=\tau-p+1}^{\tau}\hat{\Delta\theta}_r+\lambda h_{j\tau-p}+\left(\varphi_\tau-\varphi_{\tau-p}\right)\mu_0+\Delta\varepsilon_{j,(\tau,\tau-p)},\end{aligned} \tag{13}$$

where

$$\lambda=\frac{W_\tau}{W_{\tau-p}}-1=\frac{1+\tau-p+\frac{\sigma_\varepsilon^2}{\sigma_{\theta|0}^2}}{1+\tau+\frac{\sigma_\varepsilon^2}{\sigma_{\theta|0}^2}}-1=\frac{-p}{1+\tau+\frac{\sigma_\varepsilon^2}{\sigma_{\theta|0}^2}}\left(=-pW_\tau\right)<0$$

and

$$W_{\tau-p}\left(n,\sigma^2\right)\sum_{r=1}^{\tau-p}\hat{\Delta\theta}_r$$

is approximated by $h_{j\tau\text{-}p}$.

In estimation of (13), some technical problems occur. Since $h_{j,\tau}$ is bounded in [0,1], its overtime difference $\Delta h_{j(\tau,\tau\text{-}p)}$ is bounded in [-1,1]. The magnitude and sign of $\Delta h_{j(\tau,\tau\text{-}p)}$ depend on $h_{j,\tau\text{-}p}$; $\Delta h_{j(\tau,\tau\text{-}p)} \geq 0$ if $h_{j,\tau\text{-}p} = 0$ and $\Delta h_{j(\tau,\tau\text{-}p)} \leq 0$ if $h_{j,\tau\text{-}p} = 1$. For this reason, it is required to control the initial enrollment rate. To account for the censored distribution of enrollment rate difference, I use Tobit estimation with upper and lower bounds of [-1,1] for $\Delta h_{j(\tau,\tau\text{-}p)}$. I use Tobit with censored points [0,1].

In the above method, it is important to understand that returns signals used in the estimation of learning equations are estimated in the village-wise profit functions. Therefore, this estimated signal contains estimation uncertainty in the first stage (see Murphy and Topel 1985). To cope with this problem and correct standard error estimates for the parameters of interest in the second stage, I instead take the following simulation-based procedure (see Petrin and Train 2002), first drawing repeatedly and independently

schooling returns for each village, given the estimated returns and their standard errors under the normality assumption. This replication is conducted 100 times for each village (202 villages). Note that they are independent across villages. Second, the learning equations are estimated with these simulated returns signals. The standard deviations of the estimated parameters in the learning equations in this experiment, representing the estimation uncertainty that arises from the first stage, are used to correct the standard errors in the second stage.

Identification: Social Learning versus Learning by Doing

Positive response of child schooling to village-specific schooling returns implies both social learning and learning by doing. Suppose that returns to schooling increase in a village. Households can delegate decisionmaking to each individual and find who can manage the best. If the educated can do better than the uneducated, each household can learn schooling returns by this experimentation, without learning from their neighbors. Hence, in both social learning and learning by doing, we can observe positive effect of schooling returns on child schooling.

To identify social learning against learning-by-doing, I use a subsample of households in which heads have no education at all. In this group, I conjecture that children cannot learn about schooling returns from previous generations. Therefore, social-learning effect must be detected (if it exists) for this group of households.

In addition, knowing the specific roles that neighborhood factors play are also useful to identify the characteristics of social learning. In household-level learning-by-doing, neighborhood factors do not matter in the response of school enrollment to return signals.

4. Data

Data come from the National Council of Applied Economic Research (NCAER), Additional Rural Incomes Survey (ARIS), India, which covers a nationally representative

sample of rural households over three crop years: 1968-69, 1969-70, and 1970-71. A unique feature of the data is that India during this period was experiencing the onset of the Green Revolution. Farm households in some regions, therefore, are in substantial disequilibrium where returns to schooling had changed in response to the availability of imported new HYVs for wheat and rice (Rosenzweig 1990). Also, regional variations in the adoption rates of HYV seeds (see Rosenzweig 1990, and also Munshi 2004) enabled the identification of such a technical change effect on schooling returns. Due to sampling strata of ARIS data, about one-third of sample households reside in districts where the government of India implemented the Intensive Agricultural District Program, designed to facilitate the adoption of HYV technology. It is therefore possible to investigate how households altered schooling investments in response to potentially rising returns to schooling.

The second important feature of ARIS panel data for the purpose of this study is that villages in which households reside are identified in the sample. Villages are not adjacent to each other. After selecting farm households whose heads had been cultivators throughout the three years, I have 2,532 households in 253 villages. Therefore, schooling distribution, number of farm households, and measures of income-shock variance can be constructed and identified by village. In particular, sampling weights in ARIS can be used to construct each of these village characteristics. By construction, I cannot compute return signals for villages where all sample households belong exclusively to the educated or the uneducated group because the estimated proportion of educated households will be 1 or zero for these villages. Therefore, in estimation of human capital investment rule, I use only those villages in which sample households come from both groups.

ARIS data contain information on production and household characteristics. The summary statistics of the major variables I used for the estimation of profit function and human-capital investment rule are summarized in Table 1.

To construct signals on schooling returns, as discussed in the previous section, I first estimate farm profit function using information on crop profit and input variables.

Although investments were surveyed over the three years, the information on asset stocks was collected only in the final round, 1970-71. Therefore, I can construct stock data for previous years by subtracting investments from the final year's stock. This process may accumulate measurement errors in the constructed stock variables for 1968-69 and 1969-70. The variables used for profit function estimation are all normalized by cropland. In ARIS, the observations with gross cropland normalized as 1 (which corresponds to zero acres used for farming) are excluded from estimation, because these observations produce clear outliers in farm profit per unit of land.

Table 1—Descriptive statistics

	1968-69	1969-70	1970-71
Crop income	2,014.38	2,292.81	2,477.13
	(2,481.26)	(2,676.37)	(2,853.89)
Gross cropland	308.94	310.72	333.40
	(345.52)	(340.50)	(364.34)
HYV	652.93	150.65	846.86
	(3,348.61)	(49.60)	(2,099.47)
Irrigation asset	783.37	799.40	892.85
	(2,088.51)	(2,093.01)	(2,322.79)
Enrollment rate	0.3556		0.3027
	(0.4220)		(0.3929)
More than primary			0.3703
			(0.4830)
Village-level variables (n = 203)			
Proportion of educated households		0.4313	
		(0.3290)	
Schooling returns		0.2243	
		(4.826)	
Standard errors of schooling returns		1.4344	
		(1.915)	

Notes: The numbers in parentheses are standard deviations. Enrollment rate is that of children aged 5 to 14. Some observations that show enrollment rate larger than 1 are excluded. Education is the indicator that takes the value of 1 if the highest level of education attained among household members is more than primary school and zero otherwise. For the construction of village characteristics, see Section 3.

The information on child school enrollment was collected in the first and third rounds, 1968-69 and 1970-71. In estimation, child school enrollment rates for children aged 5-14 is used as a measure of child schooling. In ARIS, children are grouped in three

age-sex categories: boys aged 10-14, girls aged 10-14, and children aged 5-9. For each group, the number of enrolled children is recorded in the data. I can therefore compute household-wise average enrollment rates and group-specific enrollment rates.[19] Primary schools in India educate children aged 6-14. Since I use the indicator for schooling beyond primary level, this indicator does not pertain to children in primary school. Households with no children and inconsistent figures are dropped in preliminary stages. Through this process, sample size becomes 2,020 for the third round and 2,018 for the first round. Merging the third and first rounds, sample size becomes 1,803.[20] To take advantage of this panel structure, a difference of household-specific child enrollment rate is taken between the first and third rounds.

5. Empirical Results

Schooling Returns

As schooling variable in ARIS is categorical, I use a binary measure $1(k_j = H)$, which takes the value of 1 if the highest schooling in a household is above primary and zero otherwise. By construction, it is impossible to estimate the village-specific returns for villages where all sample households are either educated or uneducated. The number of villages to be used in the analysis is 202. As discussed, I estimate the profit function (per unit of cropland) with the highest schooling indicator, irrigation asset (per unit of cropland), and year fixed effects for each village.

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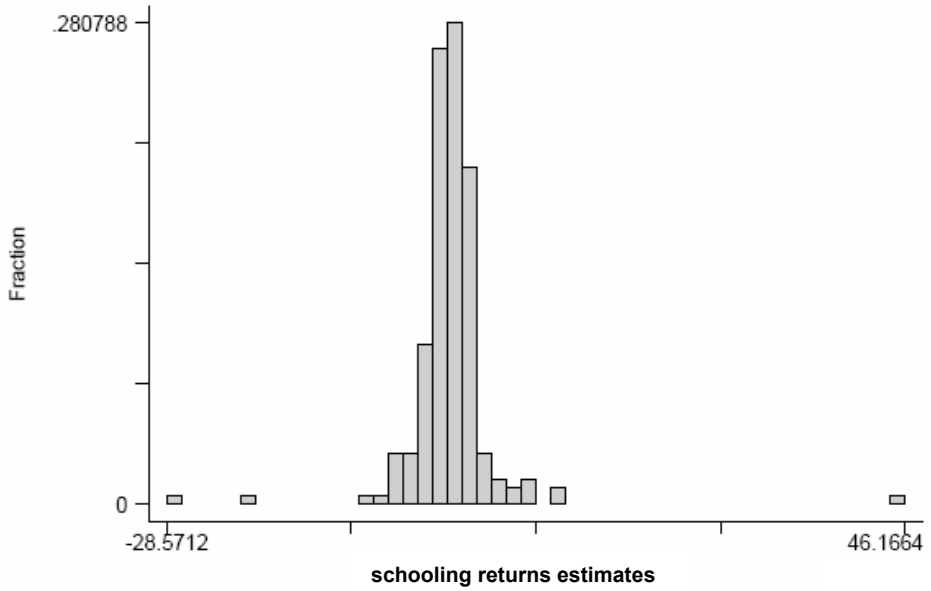
[19] In a preliminary analysis in which boys aged 10-14, girls aged 10-14, and children aged 5-9 are treated separately in enrollment rate, boys' enrollment rate is found to be more responsive to return-differential signals than girls' enrollment rate. The role of boys, especially firstborn, might be important in agricultural production, because land is usually inherited by the firstborn son. However, the framework of this paper is not appropriate for addressing gender issues in agricultural production.

[20] In sample villages, a certain proportion of residents are agricultural labor households. Households could learn about return differentials from both farm and agricultural labor households. However, because technical change considered here directly affected farm productivity in the first order and the earnings for agricultural labor only in the second order (see Foster and Rosenzweig, 2001), it is justified that the information source for schooling returns in this new technology regime is a group of farm households in villages. Furthermore, farm household mobility is negligible.

Figure 1 shows the distribution of the estimated village-specific schooling returns. A similar distribution is also obtained when I use a different specification of profit function with farm equipment, farm asset, and livestock. Therefore, we may assert that the distribution of schooling returns is stable in our sample villages. To know the effect of HYV availability on the estimated village-specific schooling returns, I estimate γ in $\hat{\Delta\theta_v^s} = \gamma_0 + \gamma \bar{HYV}_{v,0} + \eta_v$ where $\bar{HYV}_{v,0}$ is the (weighted) average of HYV adopted in the initial year. It was 0.002657 with t-value: 1.37 and R-squared: 0.0097. Though statistical significance is low, it is consistent with Foster and Rosenzweig's (1996) result that technical change increased returns to schooling at primary education.

Figure 1—Distribution of village-specific schooling returns



Learning-Investment Rule Estimates

Table 2 summarizes the results of the human-capital investment rule, using estimated village-specific schooling returns. The specifications include initial gross cropland, demographic variables, the highest-education indicator, and school dummy as control variables. The sample consists of households where heads (parents) have no

education at all to identify social learning. As discussed, the standard errors were corrected to incorporate estimation uncertainty from the first stage. Columns 1-4 use enrollment rate in 1970-71 as a dependent variable, equation (12).

Table 2—Learning and schooling investments

	Enrollment rate in 1970/71				Enrollment rate change 1968/69 to 1970/71			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Schooling returns	0.0142	0.0234	-0.0399	-0.0897	0.0070	0.0120	0.0014	-0.0224
	(0.0102)	(0.0137)	(0.0292)	(0.0399)	(0.0044)	(0.0053)	(0.0114)	(0.0159)
Proportion of educated households		0.3842	0.4303	0.3834		0.1009	0.1049	0.0905
		(0.1654)	(0.1678)	(0.1679)		(0.0630)	(0.0634)	(0.0634)
Returns variance		-0.0027	0.0002	0.0066		-0.0015	0.0016	0.0049
		(0.0020)	(0.0058)	(0.0094)		(0.0008)	(0.0019)	(0.0034)
Schooling returns * Prop			0.1483	0.4810			0.0354	0.1982
			(0.0560)	(0.2388)			(0.0222)	(0.0995)
Schooling returns * Prop squared				-0.3798				-0.1864
				(0.2520)				(0.1074)
Schooling returns * Variance			8.74E-06	0.0016			-0.00007	0.0005
			(1.69E-04)	(0.0022)			(5.40E-05)	(7.14E-04)
Schooling returns * Variance squared				-4.50E-06				-1.64E-06
				(7.53E-06)				(2.05E-06)
Enrollment rate in 1968/69					-0.8997	-0.9121	-0.9225	-0.9138
					(0.0357)	(0.0360)	(0.0361)	(0.0361)
Pseudo R squared	0.0727	0.0765	0.0817	0.0841	0.2703	0.2736	0.2766	0.2799
Number of observations	879	879	879	879	879	879	879	879
Left censored	451				59			
Right censored	150				49			

Notes: Numbers in parentheses are standard errors. Standard errors are corrected to incorporate schooling returns standard errors in the first-stage village-wise estimation. All specifications include gross cropland, the numbers of boys and girls aged above 14, between 10-14, between 5-9, and below age 4, respectively, the number of babies aged less than 1, indicators for more than primary, school presence in village and veterinary health clinic, village population, modernity and electricity indexes, and income and expenditure deciles in the initial year.

Column 1 reports the benchmark estimate of the effect of schooling returns on enrollment rate, which is positive but insignificant. Column 2 includes the proportion of educated households and the variance of schooling returns (both specific to village). Interestingly, the former has a significant and positive effect on the enrollment rate. With this effect controlled, the significance of schooling returns effect increases.

Columns 3 and 4 include the interaction terms of schooling returns and the above neighborhood characteristics. Column 3 shows that the proportion of educated households significantly increases the effect of village-specific schooling returns on the

enrollment rate. This result is consistent with our major prediction. However, in column 4, the nonlinearity in the marginal effects was not supported. In contrast, the variance of schooling returns has no significant effect.

The specifications include the indicator of the highest schooling, initial cropland, the indicator of school presence in the village, and numbers of children in different age and gender groups and other village-level variables as controls.[21,22]

Note that there could be spurious correlations of village-specific unobservables (that affect schooling investments) and observable village characteristics (such as the above neighborhood factors of our interest) in the learning function. To overcome this problem, the differenced learning equation, equation (13), is estimated with the enrollment rate change from 1968-69 to 1970-71 as a dependent variable. The results are reported in columns 5-8.

Column 5 checks the effect of estimated schooling returns on the change in enrollment rate without any neighborhood factors. The effect is positive and significant. Column 6 includes the proportion of educated households and the variance of schooling returns. Interestingly, the proportion of educated households increases the change in enrollment rate (though insignificantly) and the variance significantly decreases the change in enrollment rate. The marginal effect of schooling returns remains significant.

Columns 7-8 include the interaction terms of these neighborhood factors and schooling returns. Most interestingly, it is found that as the proportion of educated households increases, the effect of schooling returns increases but diminishes and

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[21] Some elder siblings may have already completed higher than primary during the sample period. In this case, the restriction of our sample to those households with no member educated more than primary biases our results when this schooling decision was a result of learning.

[22] A positive effect of school presence (not shown here) indicates the availability of educational institutions also enhancing schooling investments. To remove a spurious correlation between village characteristics and schooling decisions, the presence of schools must be controlled for. This correlation may have arisen from government's (public) decisionmaking in the allocation of schools to communities that have certain characteristics. Without a school dummy for control purposes, neighborhood characteristics in the learning function could be significant since those characteristics are likely correlated with the presence of schools—public schooling investments—that increase private schooling investments.

decreases in a concave way. This result is consistent with our theoretical prediction. Other parameters are insignificant in this specification.

In Columns 5-8, the significant negative effect of the initial year enrollment rate is also consistent with our prediction, which implies that enrollment rate is converging across households over time.

Appendix Table 3 confirms the above results, using a measure of technical change. Column 2 shows a significant and positive effect of the proportion of educated households on the change in enrollment rate. Though the interaction with schooling returns is insignificant in column 3, the nonlinear effects are significant and consistent with our prediction in column 4.

There is a unique optimal schooling distribution of the parents' generation. Also, initial enrollment rate significantly reduces the growth of enrollment rate. Enrollment rate therefore seems to converge over time across villages. Based on the estimates in column 8 of Table 2, I can compute the optimal proportion of educated households that maximizes learning speed as 0.5318.[23] To take this concavity seriously, the next section demonstrates some dynamic implications of this finding.

6. Simulations: Schooling and Income Dynamics

The parameter estimates of the learning-investment rule enable simulations of dynamic paths of school enrollment rates and average household income. There are two types of exercises. First, I simulate the effects of the schooling distribution of the parents' generation on enrollment rates and household income in a village. Second, I simulate the effects of the cross-community schooling redistribution on the economy-wide averages of enrollment rate and household income. The second exercise offers macroeconomic and distributional implications of the estimates. The concavity of

[23] Aki Matsui (University of Tokyo) points out that the predicted concavity might have been derived from observations from villages where the proportion of educated households is small. For the estimation of the schooling distribution effects, however, enough observations also come from villages of relatively large *n*. See Table 1.

schooling distribution effect implies that to maximize effectiveness of social learning, a mixture of educated and uneducated households in a community is more desirable than segregation by community. If so, it is better to mix both groups in every community in order to attain the most efficient transitional dynamics of schooling and income.

These simulations involve some assumptions. First, the simulations do not incorporate changes in prior variance over the three years, and therefore the simulated enrollment rates will not converge to the upper bound. This results in the accumulation of prediction errors if enrollment rates and household incomes are simulated over long periods. To avoid such a case, simulations are restricted to a five-year period. The following simulation exercises are based on the estimates from column 8 in Table 2.

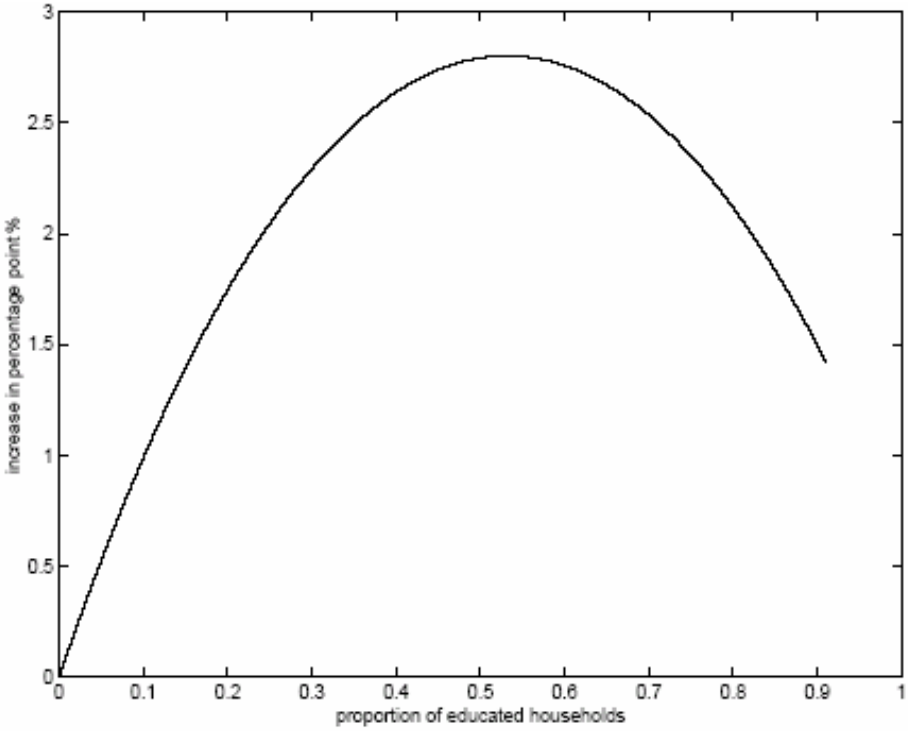
Second, since village-wise averages of return gap signals of 1969-70 and 1970-71 are used in the estimation, half of the values of each parameter are taken for simulations. The negative effect of the initial enrollment rate is not controlled in exercises below.

Intra-Village Schooling Distribution

This section quantifies the effects of intra-village schooling distribution on enrollment rate and household income. Figure 2 illustrates the simulated school enrollment rate at the end of the fifth year after a structural change for different values of the proportion of educated households.

It is assumed here that agents encounter the sample mean of return signals. The figure depicts a well-formed concave shape with the maximum increase in enrollment occurring at $n^* = 0.5318$. The figure demonstrates the quantitative importance of predetermined within-village schooling distribution of the parents' generation. For example, as the proportion decreases from n^* to 0, the enrollment-rate increase drops by about 2.75 percentage points. Though the schooling distribution effect is found to be significant in this exercise, the value of 4 percentage points of change could be overestimated because the convergence of enrollment rate to some upper bound is not assumed in the simulation.

Figure 2—The effect of schooling distribution on enrollment rate increase



The educated farm households earn, on average, a higher income than the uneducated households in this sample. I compute 315.9939 × 0.4620008 e_t, where 315.99390 is the average landholding size over the three years, 0.4620008 is the estimated marginal effect of schooling indicator on crop income per land with village fixed effects, and e_t is the enrollment rate at time t. Under this assumption, the 4-percentage point change in enrollment rate leads to the income change of 4.01 rupees.

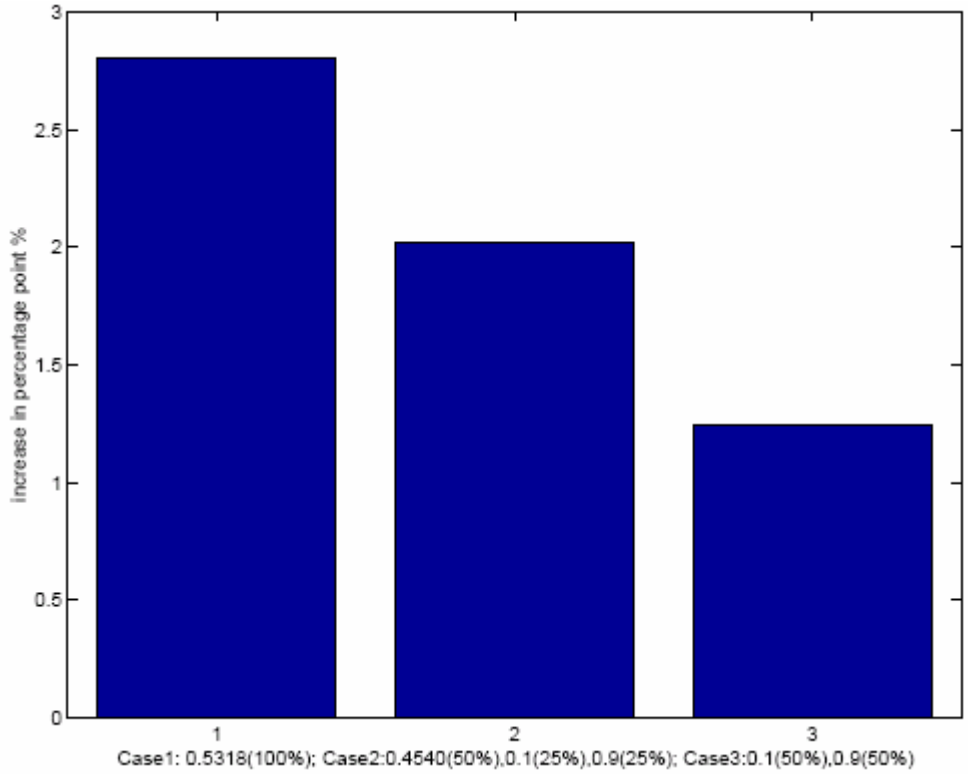
Gains from Inter-Village Schooling Reallocation

The empirical finding that inequality (rather than equality) of schooling in a community enhances social learning provides an interesting macroeconomic implication: given a finite number of educated agents in an economy, intra-community schooling distributions should be similar across communities to maximize the aggregate learning

speed. In this section, I experiment with three cases of cross-community schooling distributions to quantify the effect on the economy-average enrollment rate increase. The cases that I consider here are as follows: (1) all villages have the best proportion of the educated, 0.5318; (2) 50 percent of villages have a proportion of educated households equal to 0.5318, 25 percent of villages have a proportion of 0.9, and 25 percent of villages have a proportion of 0.1; and (3) 50 percent of villages have a proportion of 0.9, and 50 percent of villages have a proportion of 0.1. Note that the economy average of the proportion of the educated is almost the same in the three cases.

Figure 3 shows increases in the economy-wide average enrollment rate in the fifth year after a change in returns. It is predicted that the stronger the concavity of learning function in *n*, the more divergent the three cases. At the end of the fifth year after a structural change, the average enrollment rate rises nearly by 2.75 percentage points in

Figure 3—Economy-average enrollment rate increase (percent point)



the degenerate case (case 1) and it rises by 1.25 percentage points in the complete segmentation case (case 3). The aggregate response of human-capital investments toward a rise in schooling returns varies by nearly 1.5 percentage points as the cross-community allocation of schooling moves from complete integration to complete segmentation.

7. Conclusions

This paper shows that neighborhood factors matter in schooling investments, with evidence from farm household panel data from the Green Revolution in India. In the face of the HYV availability that altered schooling returns, agents learned of the benefits of new returns to schooling from neighbors and adjusted schooling investments over time. In this context, the empirical results clarify the importance of schooling distribution of the parents' generation within a community. Heterogeneity of schooling increases informativeness of the community when it encounters a change in schooling returns, since agents easily compare differentially educated agents. The homogeneous community with few differences in schooling makes it hard to identify the effects of schooling. This intuitive prediction was supported in the empirical analysis of this paper.

To increase learning efficiency in a society, should the educated and uneducated be integrated or segregated by communities? Our findings imply that integration of the two populations in a community is more desirable. Intuitively, given that a mixture of the two groups in a neighborhood enables the comparison between the groups—schooling returns, in this paper—all communities should be heterogeneous. This implication is against a common finding on positive sorting in residential choice behavior (e.g., Fernandez 2001). If agents are sorted by their types, including education, in the choice of their residential areas, the population becomes more homogeneous in a community and weakens the response of schooling investments to a change in schooling returns. If social learning effects are not internalized in agents' location choice, the evidence of this paper justifies a socially desirable policy intervention. This implication

should not be exclusive to education but could equally apply to issues such as social class and the division of labor.

However, the relevance of the findings in this paper depends on the frequency of structural changes. As stated in Schultz (1975), if the benefit of education generates from situations of disequilibrium such as the Green Revolution, the augmented returns to schooling will eventually decrease as the knowledge of new technologies diffuses evenly and widely in the population. All these issues still remain unexplored and should be examined carefully in the context of developing countries.

Appendix Table

Table 3—Learning and schooling investments: Robustness check

Dependent: change in enrollment rate 1968-69 to 1970-71				
Schooling returns (explained by mean HYV)	3.9675	3.4515	16.9964	-39.0464
	(0.38)	(0.34)	(0.90)	(1.37)
Prop educated households		0.2948	0.3170	0.3459
		(3.91)	(3.97)	(4.37)
Schooling returns * Prop			-29.344	301.005
			(0.89)	(2.29)
Schooling returns * Prop squared				-343.625
				(2.60)
Enrollment rate in 1968-69	-0.7874	-0.7856	-0.7847	-0.7831
	(16.71)	(16.94)	(16.92)	(17.02)
Pseudi R squared	0.2593	0.2726	0.2732	0.2792
Number of observations	473	473	473	473

Notes: Numbers in parentheses are absolute t values. The numbers of observations left censored and right censored are 30 and 23, respectively. The sample is restricted to those villages where the mean of HYV adopted in the initial year was strictly positive and the estimated returns in the last year were less than 0.02 (to exclude outlying observations). Schooling returns are the average of returns estimates predicted by the average HYV adopted in 1969-70 and 1970-71 in each village. For details, see Sections 3 and 4. All specifications include gross cropland, the numbers of boys and girls aged above age 14, aged 10-14, aged 5-9, and below age 4, respectively, the number of babies aged less than 1, indicators for more than primary, school presence in village and veterinary health clinic, village population, modernity and electricity indexes, income, and expenditure deciles in the initial year.

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